Fourier Theory

and

Filtering in spectral and spatial domains

Image processing methods may be broadly divided into two categories:

Real space methods

-- which work by directly processing the input pixel array.

Fourier space methods

-- which work by firstly deriving a new representation of the input data by performing a *Fourier transform*, which is then processed, and finally, an *inverse Fourier transform* is performed on the resulting data to give the final output image.

What do frequencies mean in an image?

If an image has large values at *high* frequency components then the data is changing rapidly on a short distance scale. (*e.g.,* a page of text).

If the image has large *low* frequency components then the large-scale features of the picture are more important (*e.g.* a single fairly simple object which occupies most of the image).

Fourier Theory

The tool, which converts a spatial (real space) description of an image into one in terms of its frequency components, is called the Fourier transform. The new version is usually referred to as the Fourier space description of the image.

The corresponding *inverse* transformation which turns a Fourier space description back into a real space one is called the inverse Fourier transform.

1D Case:

Considering a continuous function *f*(*x*) of a single variable *x* representing distance. The Fourier transform of that function is denoted *F*(*u*), where *u* represents spatial frequency is defined by:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi xu} dx$$

Note: In general *F*(*u*) will be a complex quantity *even though* the original data is purely real.

The meaning of this is that, not only is the magnitude of each frequency present important, but that its phase relationship is too.

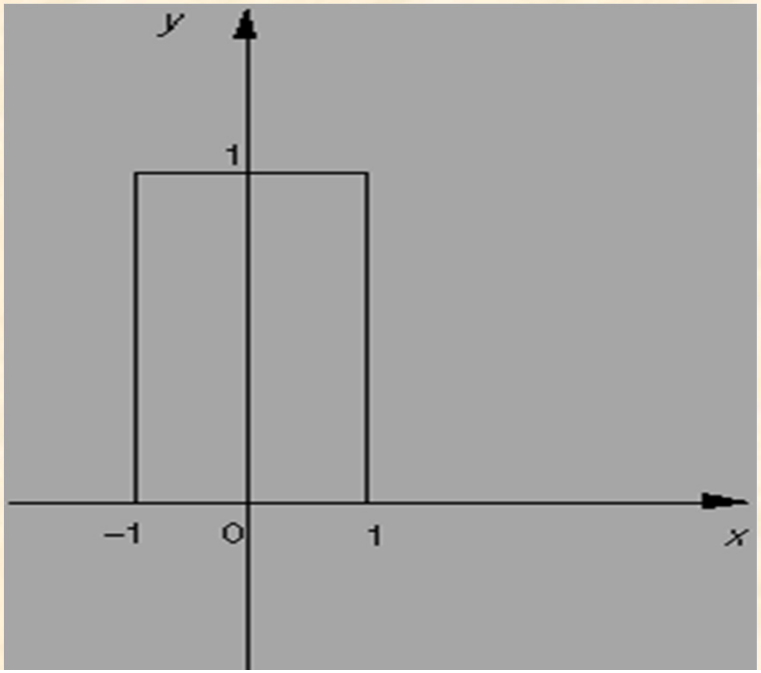
The inverse Fourier transform for regenerating *f*(*x*) from *F*(*u*) is given by:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi xu} du$$

which is rather similar, except that the exponential term has the opposite sign.

Let's see how we compute a Fourier Transform: consider a particular function *f*(*x*) defined as :

$$f(x) = \begin{cases} 1, & if \ |x| \leq 1 \\ 0, & otherwise \end{cases}$$

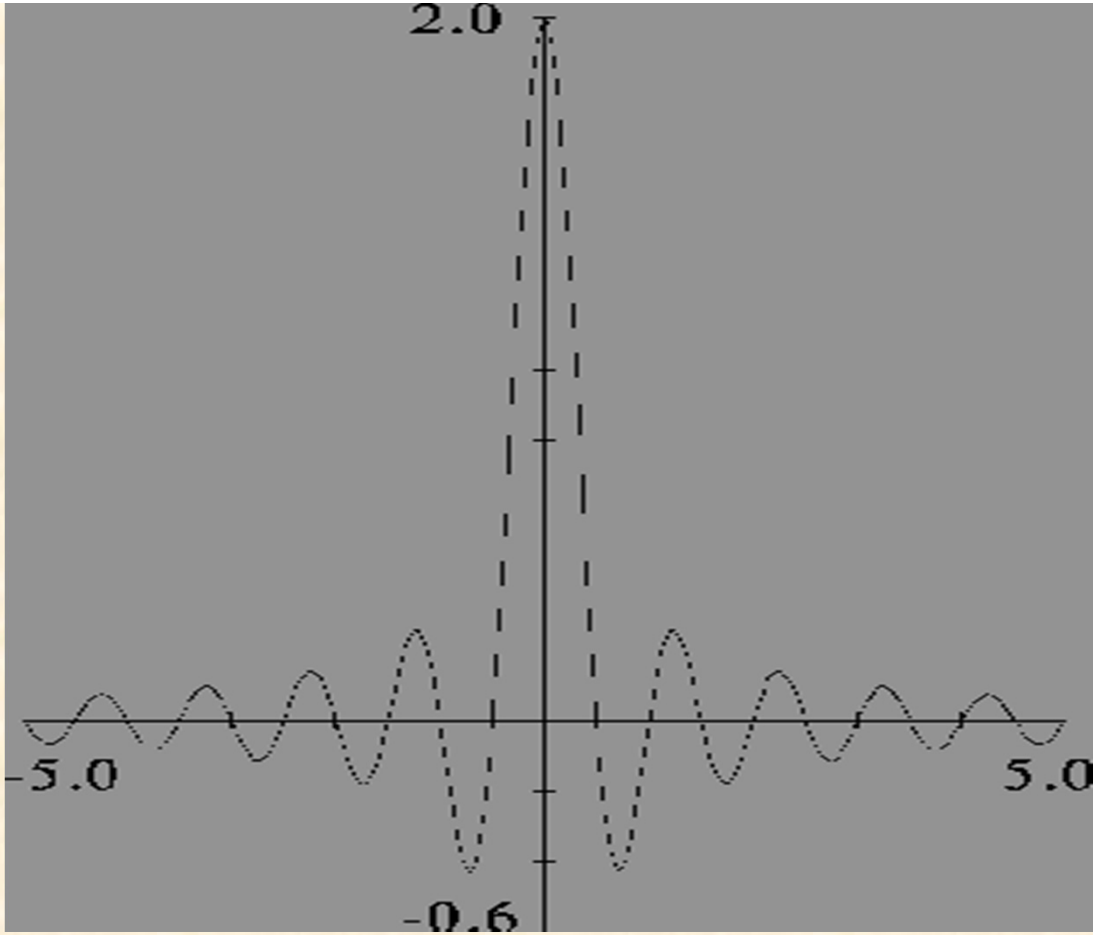


$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi xu} dx$$

$$= \int_{-1}^{1} e^{-j2\pi ux} dx$$

$$= \frac{-1}{j2\pi u}(e^{-j2\pi u} - e^{j2\pi u})$$

$$= \frac{\sin 2\pi u}{\pi u}$$



In this case *F*(*u*) is purely real, which is a consequence of the original data being symmetric in *x* and *-x*. This function is often referred to as the *Sinc function*

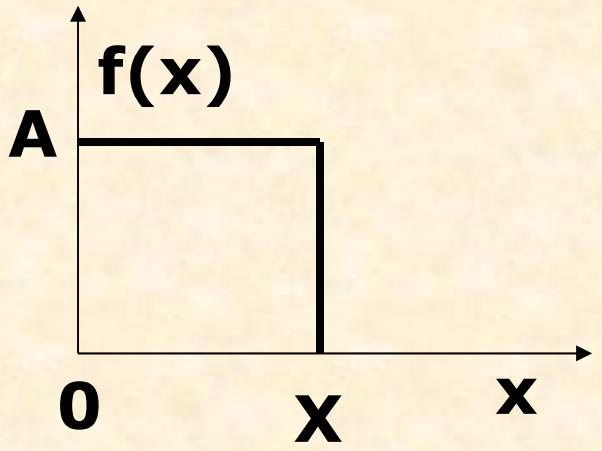
$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi xu} dx$$

$$= \int_{0}^{X} A e^{-j2\pi ux} dx$$

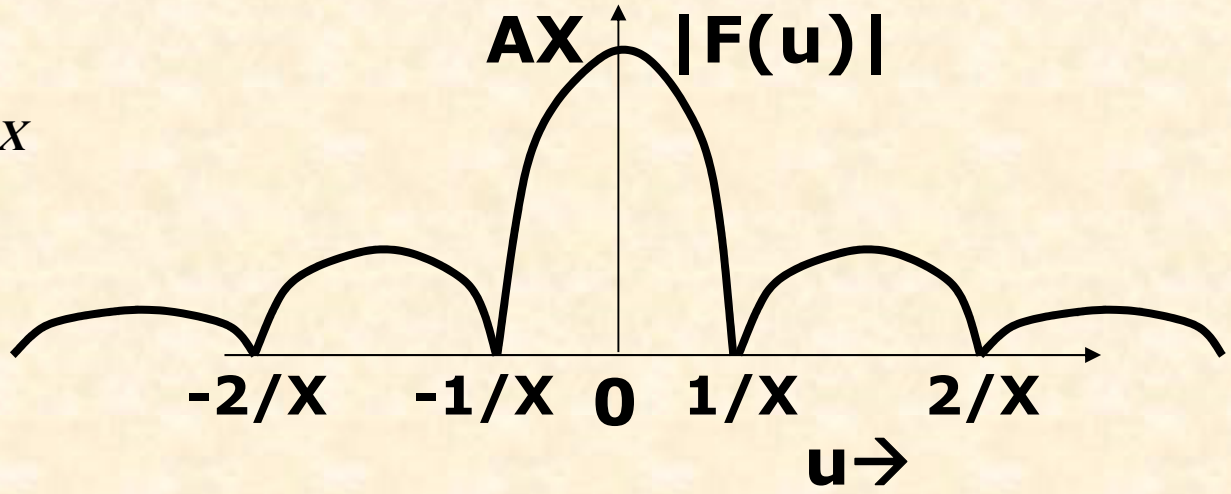
$$= \frac{-A}{j2\pi u} [e^{-j2\pi ux}] \Big|_0^X$$

$$= \frac{-A}{j2\pi u} (e^{j2\pi uX} - 1)$$

$$= \frac{A}{\pi u} \sin(\pi uX) e^{-j\pi uX}$$



$$|F(u)| = AX \left| \frac{\sin(\pi uX)}{\pi uX} \right|$$



$$F(u) = R(u) + jI(u) \qquad |F(u)| = \sqrt{R^2(u) + I^2(u)};$$

$$= |F(u)| e^{j\phi(u)}; \qquad \phi(u) = \arctan[I(u)/R(u)]$$

|F(u)| is called the magnitude spectrum and ϕ(u) is called the phase angle (phase spectrum).

$$P(u) = |F(u)|^2 = R^2(u) + I^2(u)$$

is called Power spectrum or spectral density.

Use:

$$D(u) = c \log(1 + |F(u)|)$$

for display purpose only.

Same hold for 2-D

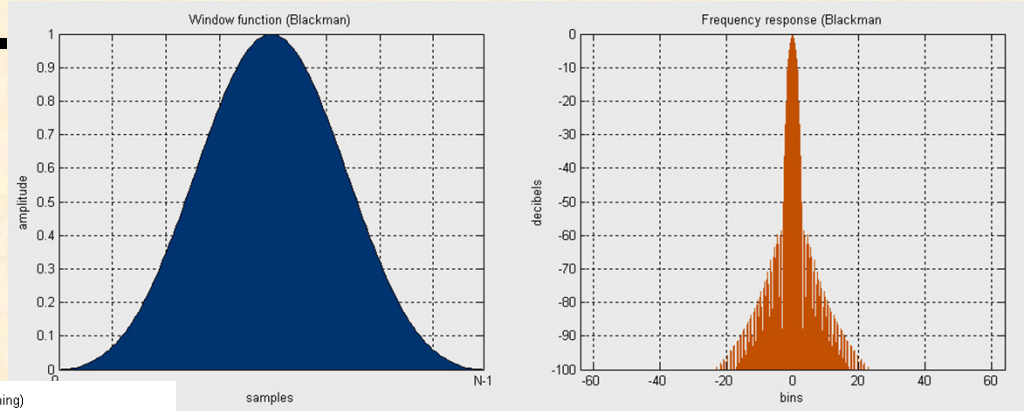
Partial list of spectral density estimation techniques:

$$F_w(\omega) \equiv \int_{-\infty}^{+\infty} F(x)\, W(\omega - x)\, dx/2\pi$$

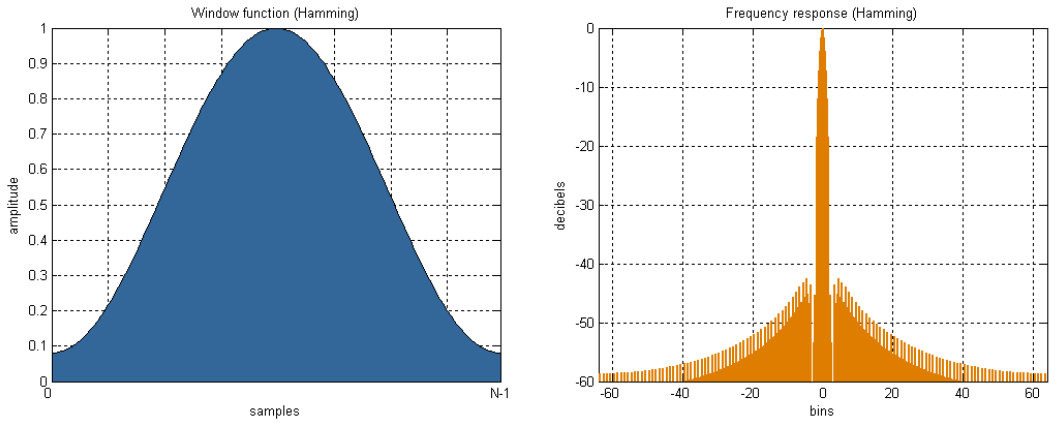
$$F_w(\omega) = F(\omega) \bullet W(\omega).$$

- **Periodogram**, a classic non-parametric technique
- **Autoregressive moving average** estimation, based on fitting to an **ARMA** model
- **Least-squares spectral analysis**, based on least-squares fitting to known frequencies.

Read about Periodogram, obtained using various windows: Triangular, Cosine, Hann, etc.



Hamming



Blackman /Kaiser/ Gaussian

2D Case - continuous

If *f*(*x*,*y*) is a function, for example the brightness in an image, its Fourier transform is given by:

$$F(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-j2\pi(ux+vy)} dxdy$$

and the inverse transform is:

$$f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u, v) e^{j2\pi(ux+vy)} dudv$$

Discrete Case - 1-D

Images are digitized - discrete sequence of numbers. Thus, we need a *discrete* formulation of the Fourier transform, which takes such regularly spaced data values, and returns the value of the Fourier transform for a set of values in frequency space which are equally spaced.

Replacing the integral by a summation, does this quite naturally, gives the *discrete Fourier transform* or DFT for short.

In 1-D it is convenient now to assume that *x* goes up in steps of 1, and that there are *N* samples, at values of *x* from 0 to *N*-1. So the DFT takes the form:

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{-j2\pi ux/N}; u = 0,1,...., (N-1)$$

while the inverse DFT is:

$$f(x) = \sum_{u=0}^{N-1} F(u) e^{j2\pi ux/N}; x = 0,1,...., (N-1)$$

NOTE: Minor changes from the continuous case are a factor of 1/*N* in the exponential terms, and also the factor 1/*N* in front of the forward transform which does not appear in the inverse transform.

The *2D DFT* works in a similar way. So for an NxM grid in *x* and *y* we have:

$$F(u, v) = \frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x, y) e^{-j2\pi(xu/N + yv/M)}$$

$$u = 0,1,...., N-1; v = 0,1,...., M-1$$

and

$$f(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u, v) e^{j2\pi(xu/N + yv/M)}$$

$$x = 0,1,...., N-1, y = 0,1,...., M-1$$

Often *N*=*M*, and it is then it is more convenient to redefine *F*(*u*,*v*) by multiplying it by a factor of *N*, so that the forward and inverse transforms are more symmetrical:

$$F(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x, y) e^{-j2\pi(xu/N + yv/M)}$$

$$u, v = 0,1,..., N - 1$$

and

$$f(x, y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u, v) e^{j2\pi(xu/N + yv/M)}$$

$$x, y = 0,1,..., N - 1$$

$$\Delta x = 1/(N.\Delta u);$$

$$\Delta y = 1/(N.\Delta v);$$

Some useful properties of Fourier Transform:

TRANSLATION

$$f(x,y)\exp[j2\pi(u_0x+v_0y)/N] \Leftrightarrow F(u-u_0,v-v_0)$$

$$f(x-x_0,y-y_0) \Leftrightarrow F(u,v)\exp[-j2\pi(ux_0+vy_0)/N]$$

$$|F(u,v)\exp[-j2\pi(u_0x+v_0y)/N]| = |F(u,v)|$$

Periodicity and Conjugate Symmetry

$$F(u,v) = F(u+N,v) = F(u,v+N) = F(u+N,v+N)$$

If f(x, y) is real, the F.T. exhibits conjugate symmetry:

$$F(u,v) = F^*(-u,-v);\ or\ |F(u,v)| = |F(-u,-v)|$$

ROTATION

Consider Polar coordinate form:

$$f(x,y) \Rightarrow f(r,\theta); \qquad F(u,v) = F(\omega,\varphi)$$

Then:

$$f(r,\theta+\theta_0) \Leftrightarrow F(\omega,\varphi+\theta_0)$$

Distributivity and Scaling

$$\boldsymbol{F}[f_1(x,y)+f_2(x,y)] = \boldsymbol{F}[f_1(x,y)]+\boldsymbol{F}[f_2(x,y)];$$

and, in general

$$\boldsymbol{F}[f_1(x,y)\cdot f_2(x,y)] \neq \boldsymbol{F}[f_1(x,y)]\cdot\boldsymbol{F}[f_2(x,y)];$$

For scalars a, b:

$$af(x,y) \Leftrightarrow aF(u,v);$$

$$f(ax,by) \Leftrightarrow \frac{1}{|ab|}F(u/a, v/b)$$

Average Value

$$\tilde{f}(x,y)=\frac{1}{N^2}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y);$$

Thus,

$$\tilde{f}(x,y)=\frac{1}{N}F(0,0)$$

From, 2 – D DFT :

$$F(0,0)=\frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y);$$

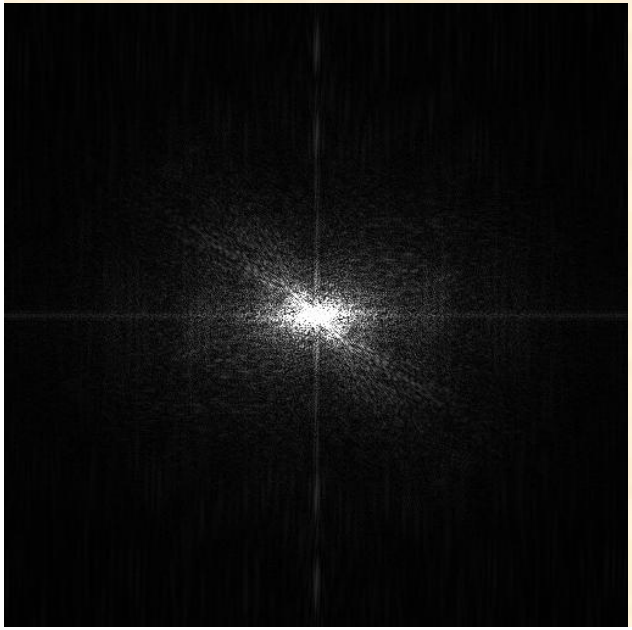
LAPLACIAN

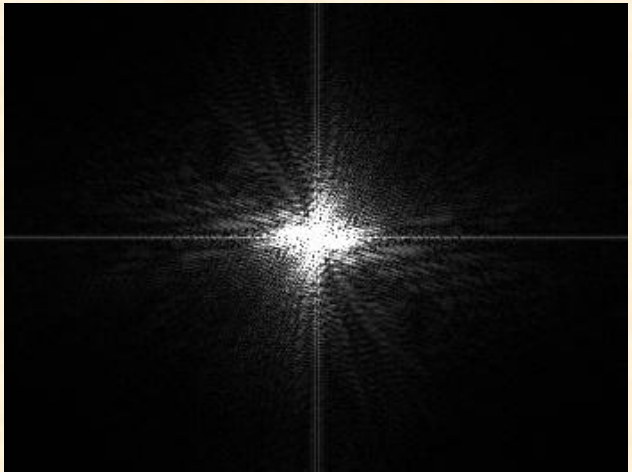
$$\nabla^2 f(x,y)=\frac{\partial^2 f}{\partial x^2}+\frac{\partial^2 f}{\partial y^2}$$

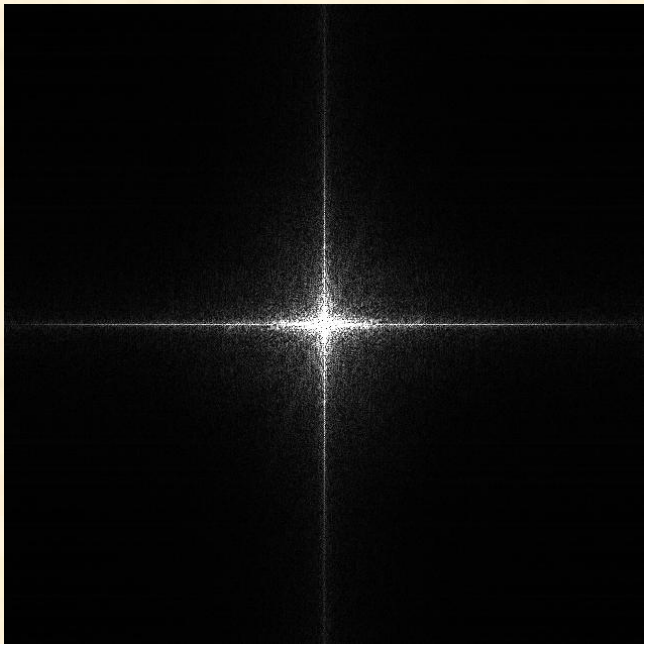
$$\boldsymbol{F}\left[\frac{d^2 f(x)}{dx^n}\right]\Leftrightarrow(2\pi ju)^n F(u)$$

$$\boldsymbol{F}[\nabla^2(f(x,y)]\Leftrightarrow-(2\pi)^2(u^2+v^2)F(u,v)$$

Digital images and their 2-D DFT's







2-D DFT using 1-D DFT

$$F(u,v) = \frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} f(x,y)e^{-j2\pi(xu/N+yv/M)}$$

$$u,v = 0,1,\ldots,N-1$$

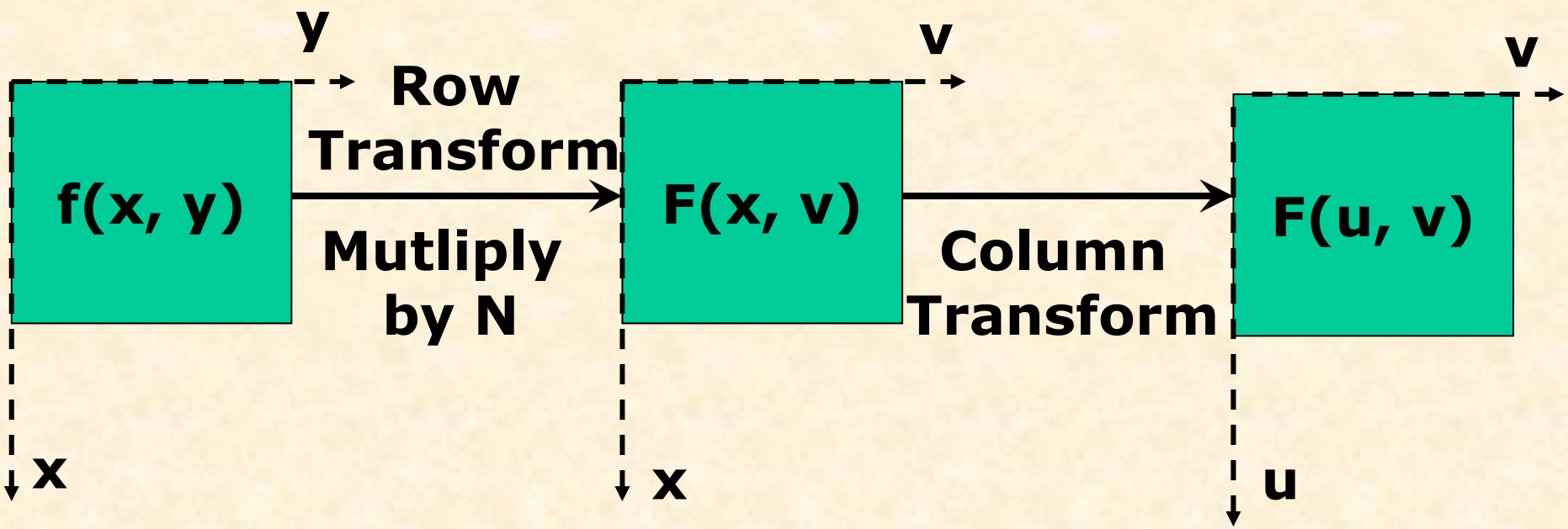
$$F(u,v) = \frac{1}{N}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} f(x,y)e^{-j2\pi(xu/N+yv/M)}$$

$$= \frac{1}{N}\sum_{x=0}^{N-1} F(x,v)\exp[-j2\pi(xu/N)]$$

where,

$$F(x,v) = N[\frac{1}{N}\sum_{y=0}^{N-1} f(x,y)\exp[-j2\pi(yv/N)]$$

2-D DFT using FFT



Assume an optimized algorithm for 1-D DFT, termed FFT, available for use.

FILTERING

LOW PASS FILTER

A 2-D ideal lowpass filter (LPF) is one whose transfer function satisfies the relation

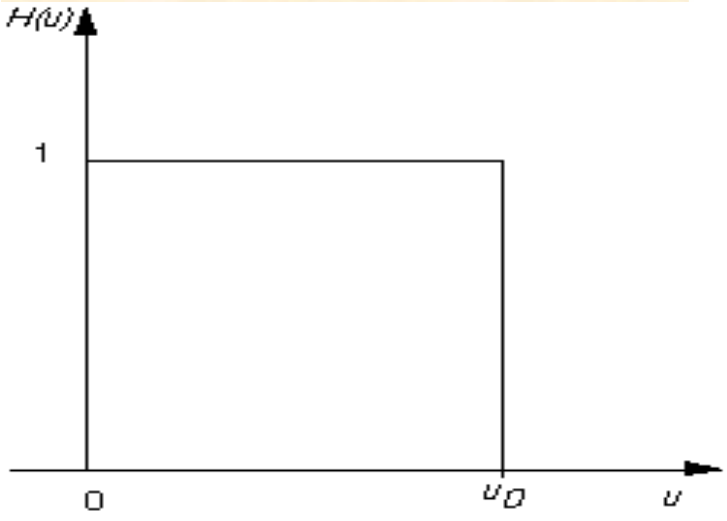
$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \le D_o \\ 0 & \text{if } D(u, v) > D_o \end{cases}$$

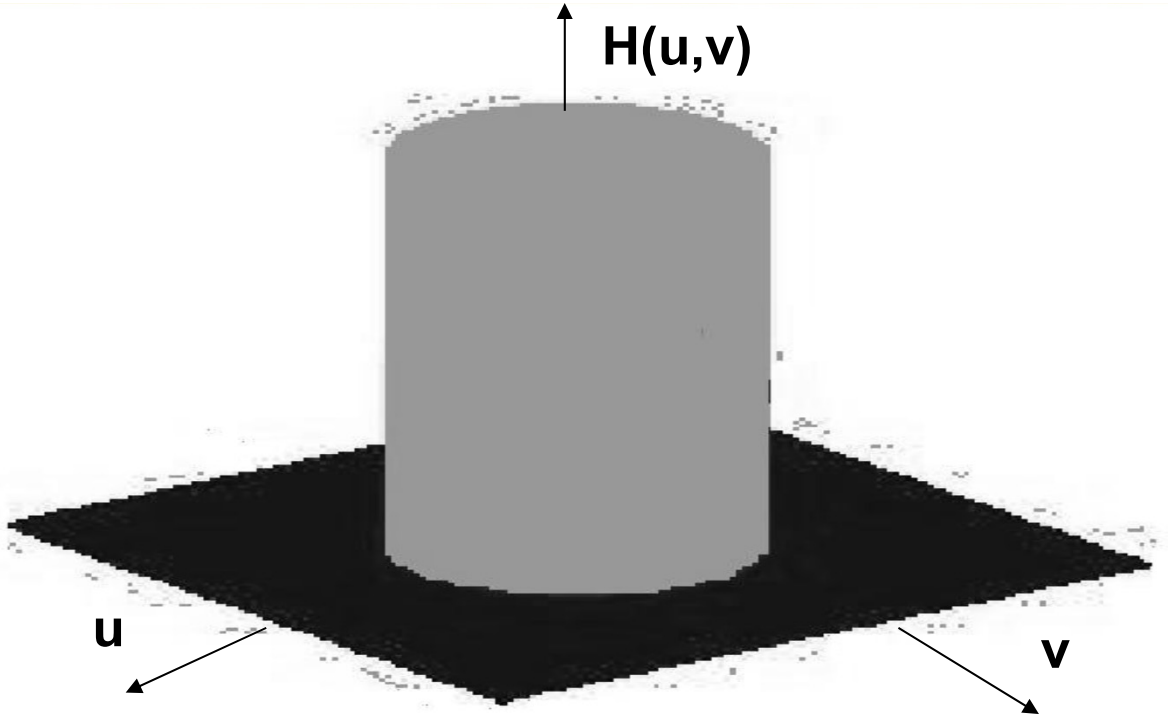
where, D_o is a specified non-negative quantity, and D(u, v) is the distance from point (u,v) to the origin of the frequency plane, that is,

$$D(u, v) = (u^2 + v^2)^{1/2}$$

Low frequency components are responsible for the slowly varying characteristics of an image, such as overall contrast and average intensity.

It blurs the image, since it de-enhances edges and other sharp details in an image which contribute to the high frequency components.





Input Image(Lena)

Low Pass Filtered Image

HIGH PASS FILTER

A 2-D ideal highpass filter (HPF) is one whose transfer function satisfies the relation

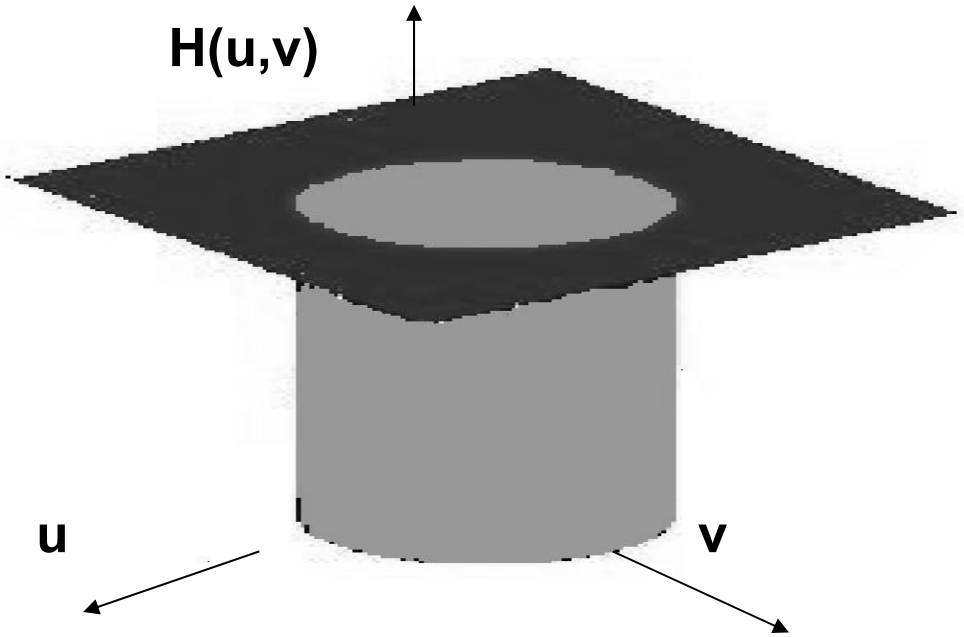
$$H(u, v) = \begin{cases} 0 & \text{if } D(u, v) \le D_o \\ 1 & \text{if } D(u, v) > D_o \end{cases}$$

Where D_o is the cutoff distance measured from the origin of the frequency plane and D(u, v) is given by

$$D(u, v) = (u^2 + v^2)^{1/2}$$

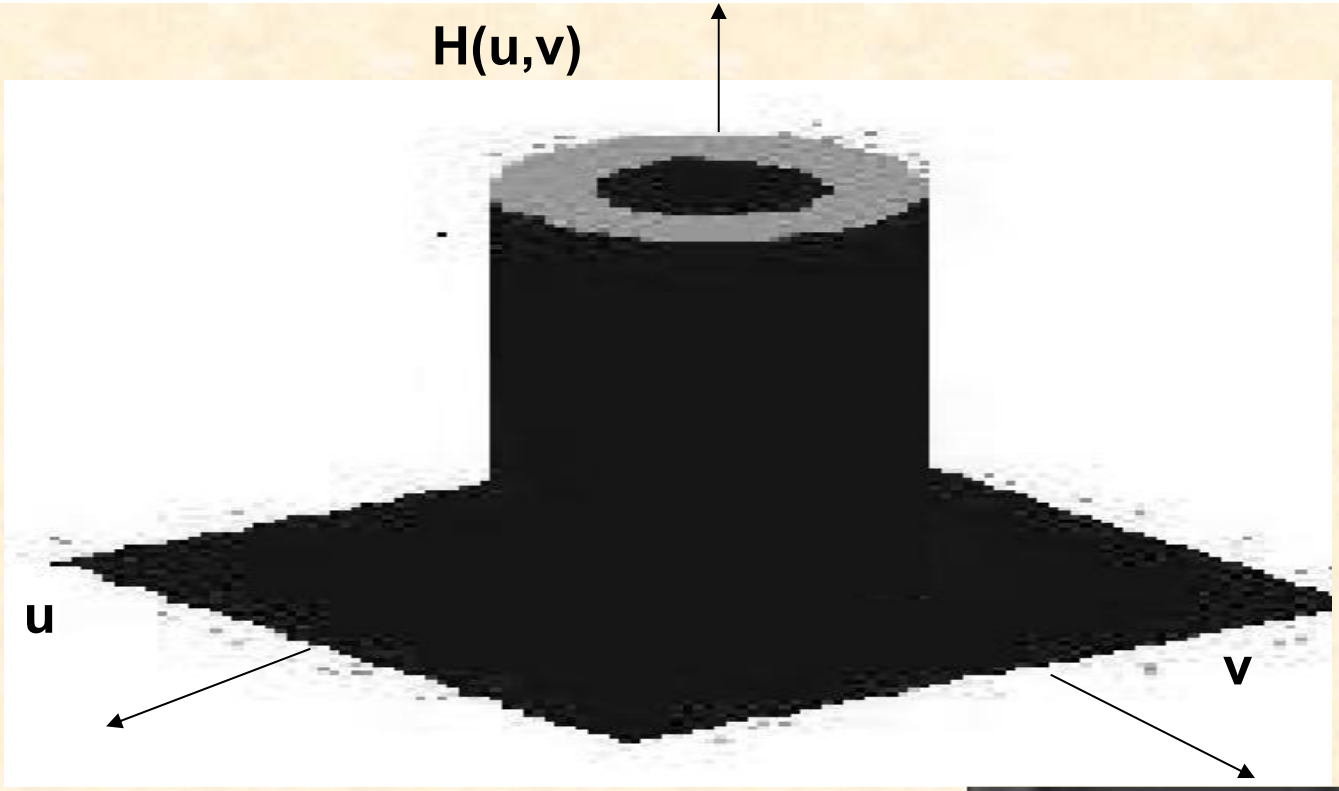
High-frequency components characterize edges and other sharp details.

Highpass filtering causes a loss in the low frequency components in the image, the smaller gray level variations in the image are removed in the output. The output image will have sharpened edges and other sharp details.



Input Image(Lena)

High Pass Filtered Image



Input Image(Lena)

Band-Pass Filtered Image

Comparison of the effects of filtering

Low Pass

Band Pass

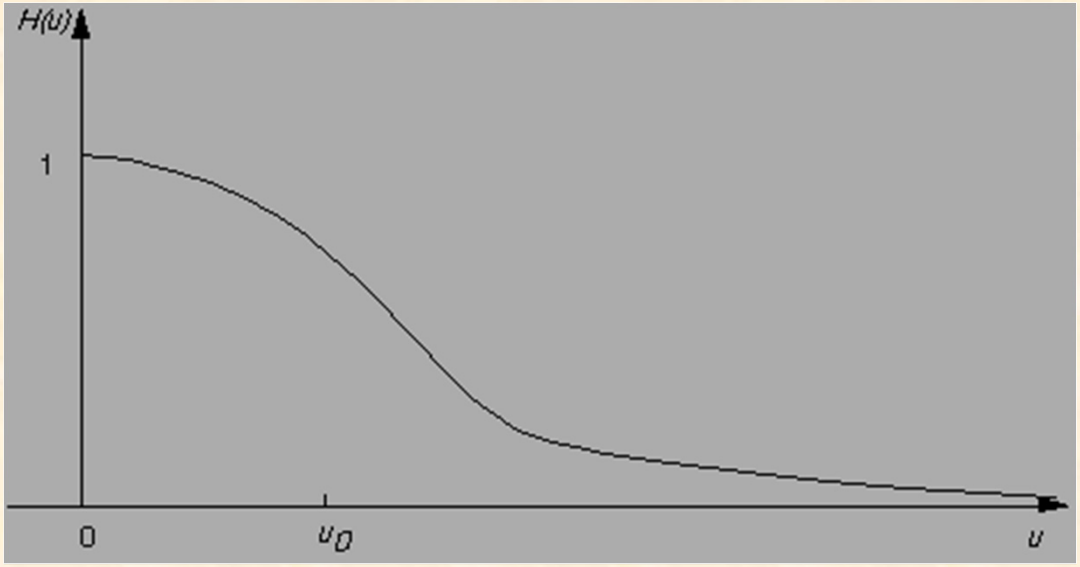
High Pass

Low Pass Butterworth Filter

Another filter sometimes used is the *Butterworth lowpass filter (BLPF)*. In this case, *H*(*u*,*v*) takes the form:

$$H(u, v) = \frac{1}{1 + [(u^2+v^2) / w_0^2]^n}$$

where, *n* is called the order of the filter. This keeps some of the high frequency information, as illustrated by the second order one-dimensional Butterworth filter shown in the figure below:



This is one way of reducing the blurring effect of an ILPF.

Wiener Filter: Adaptive Inverse Filter

Purpose: To Remove noise and/or bluriness in the image.

Estimate the local mean and variance in the neighborhood around each pixel

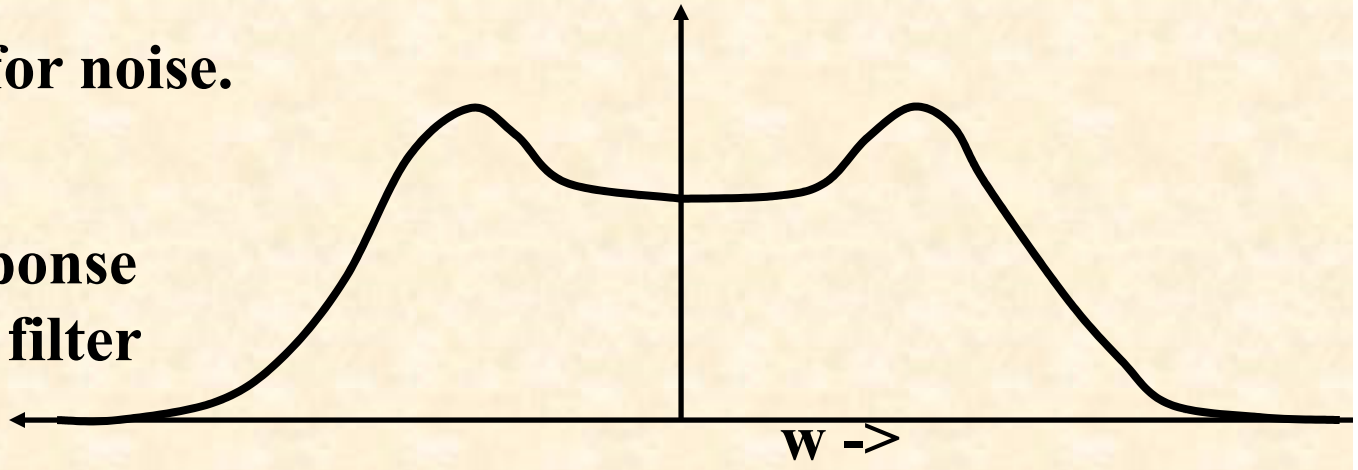
$$\mu = (1/MN)\sum f(x,y) \quad \sigma^2 = (1/MN)\sum [f(x,y)-\mu]^2$$

Wiener filter formulation, for no blur:

$$w(x,y) = \mu + \frac{\sigma^2 - n_v^2}{\sigma^2}(f(x,y)-\mu)$$

Where n_v is the standard deviation for noise.

Typical response For Wiener filter



Convolution

Several important optical effects can be described in terms of convolutions. Let us examine the concepts using 1D continuous functions.

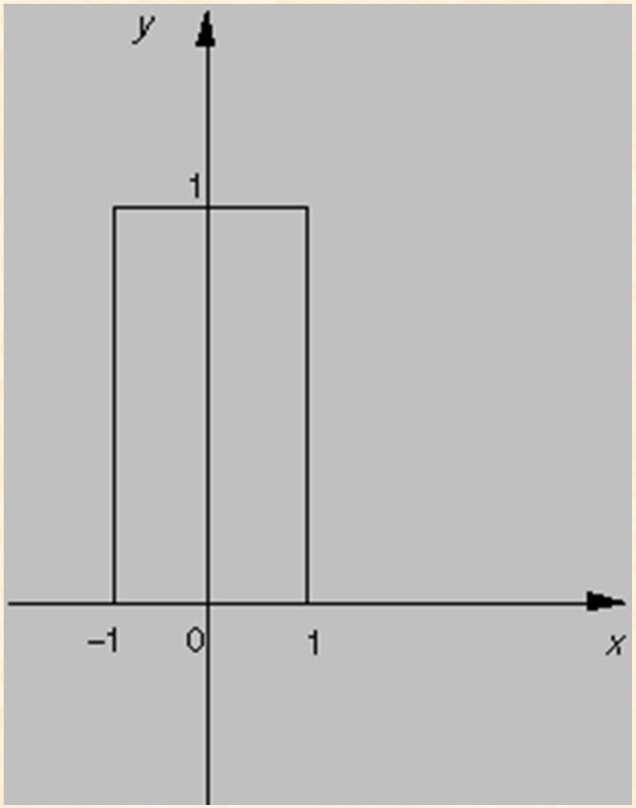
The convolution of two functions *f*(*x*) and *g*(*x*), written *f*(*x*)g*(*x*), is defined by the integral**

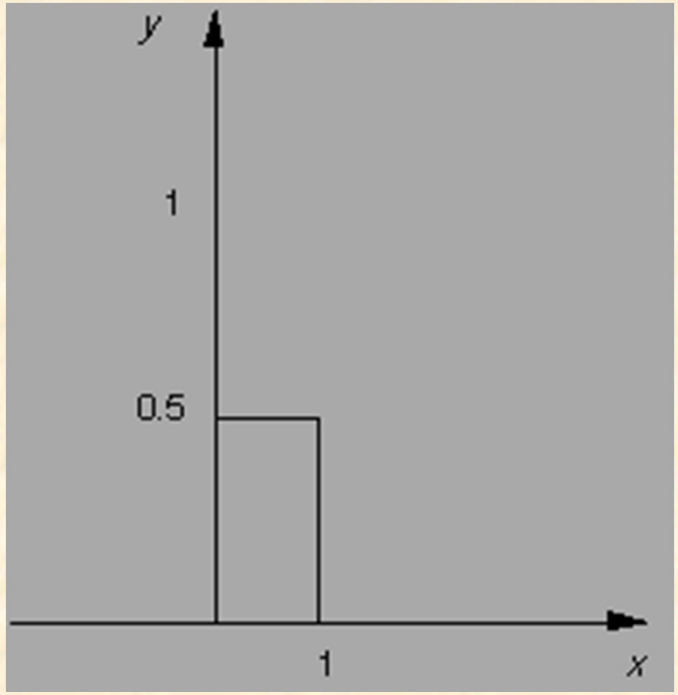
$$f(x) * g(x) = \int_{-\infty}^{\infty} f(\alpha) g(x - \alpha) d\alpha$$

For example, let us take two top hat functions. Let f(x) and g(x) be two top hat functions defined as:

$$f(x) = \begin{cases} 1, & if \ |x| \leq 1 \\ 0, & otherwise \end{cases}$$

$$g(x) = \begin{cases} 1/2, & if \ 0 \leq x \leq 1 \\ 0, & otherwise \end{cases}$$

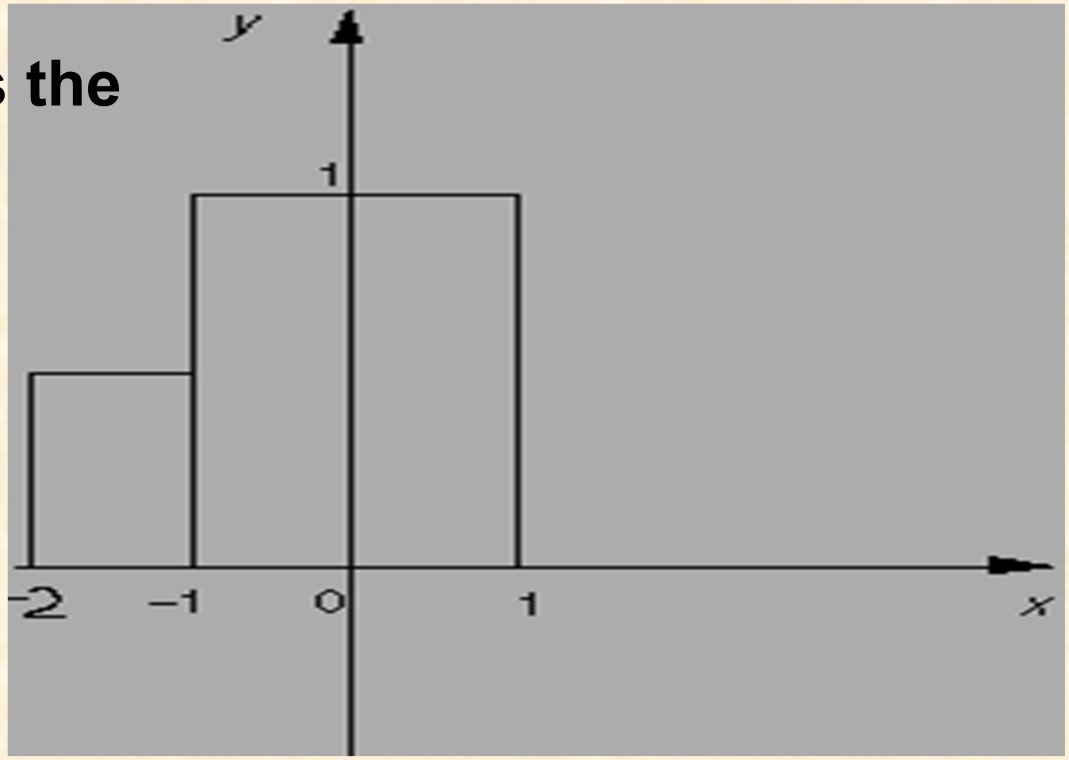




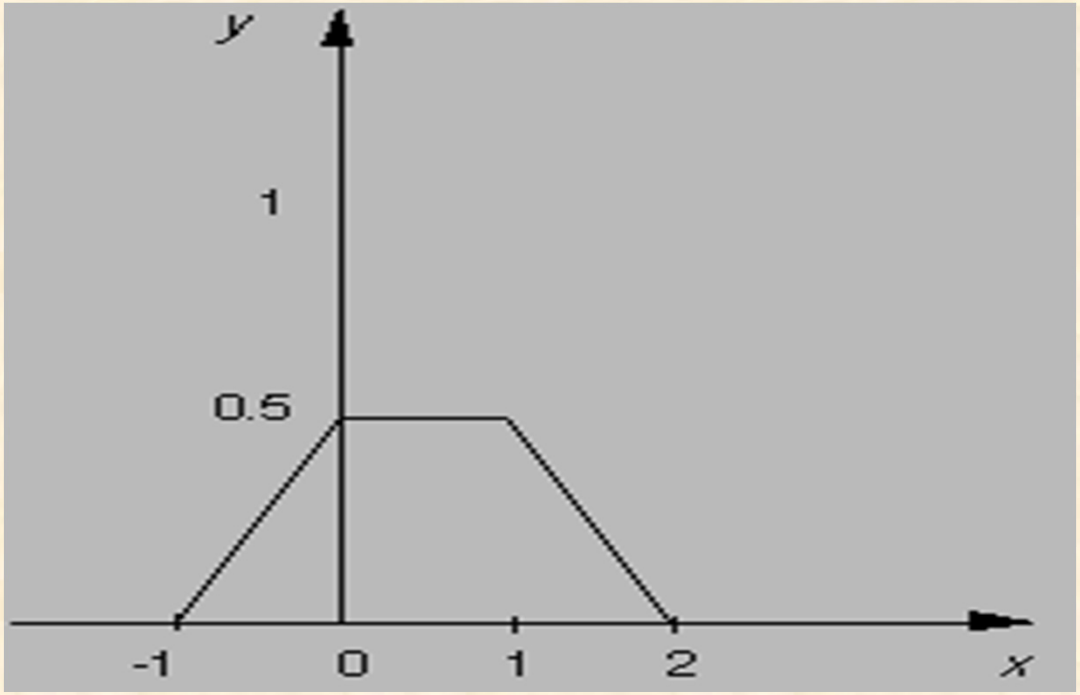
Steps:

- Form g(-α),
- Form g (x - α) by shifting/sliding,
- For any given x, get the product of f(α). g(x-α), by finding the overlap of these two functions,
- Keep repeating the above step for all values of x

Example below illustrates the situation, when x = -1:

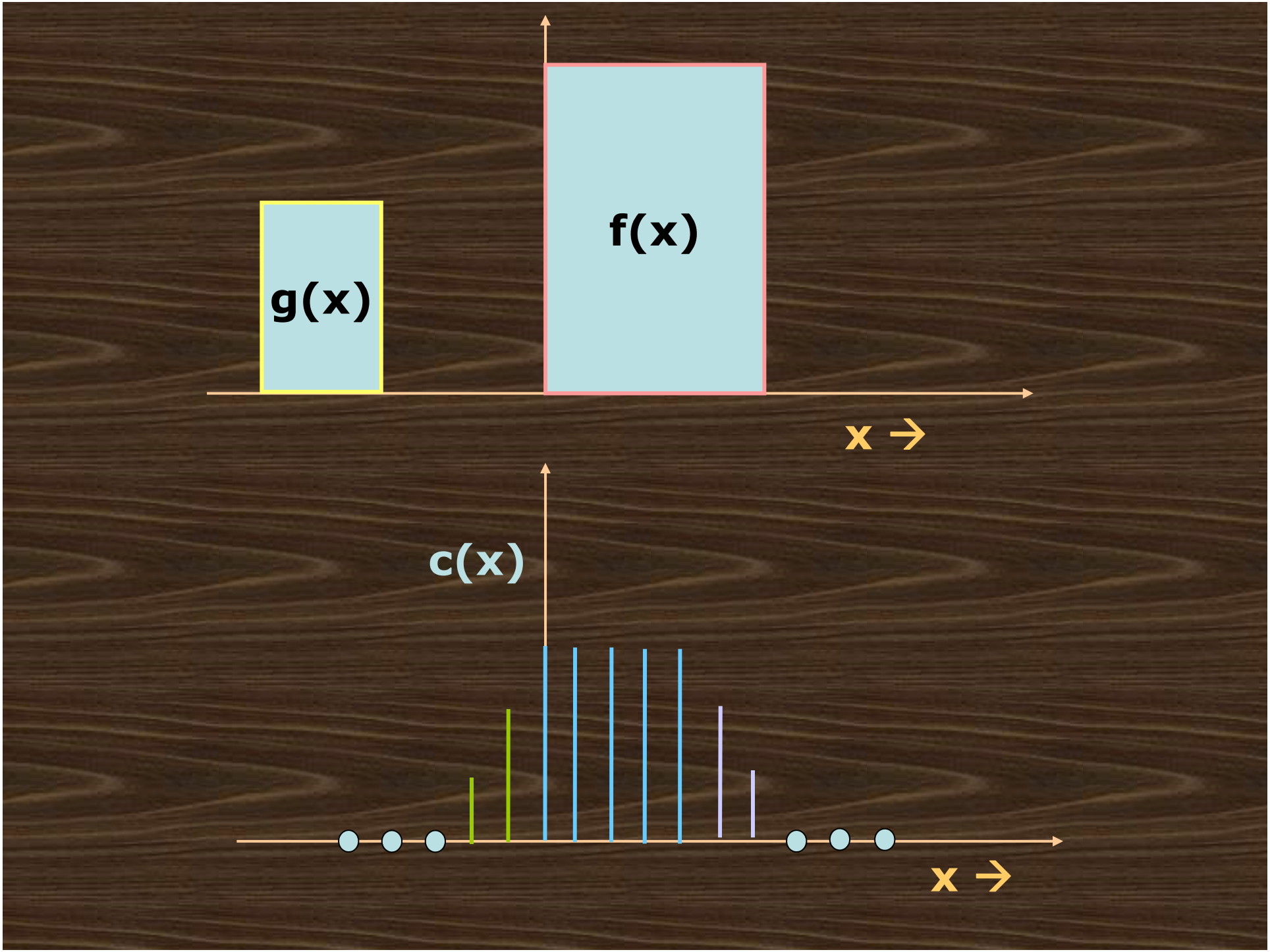


Thus the convolution of *f*(*x*) and *g*(*x*), *f*(*x*)g*(*x*), in this case has the form :**



Mathematically the output of this convolution can be expressed by:

$$f(x) * g(x) = \begin{cases} (x+1)/2 & \text{if } -1 \le x \le 0 \\ 1/2 & \text{if } 0 \le x \le 1 \\ 1 - x/2 & \text{if } 1 \le x \le 2 \\ 0 & \text{otherwise} \end{cases}$$


g(x)
f(x)
x →
c(x)
x →

Convolution in 2-D

$$1-D:\ m * f(x) = \int f(u)m(x-u)du$$

Continuous case:

$$2-D:\ m * f(x,y) = \int f(u,v)m(x-u,y-v)dudv$$

$$1-D:\ m * f(x) = \sum_i f(x-i)m(i)$$

Discrete case:

$$2-D:\ m * f(x,y) = \sum_i \sum_j f(x-i,y-j)m(i,j)$$

Correlation (discrete case):

$$1-D:\ m \bullet f(x) = \sum_i f(x+i)m(i)$$

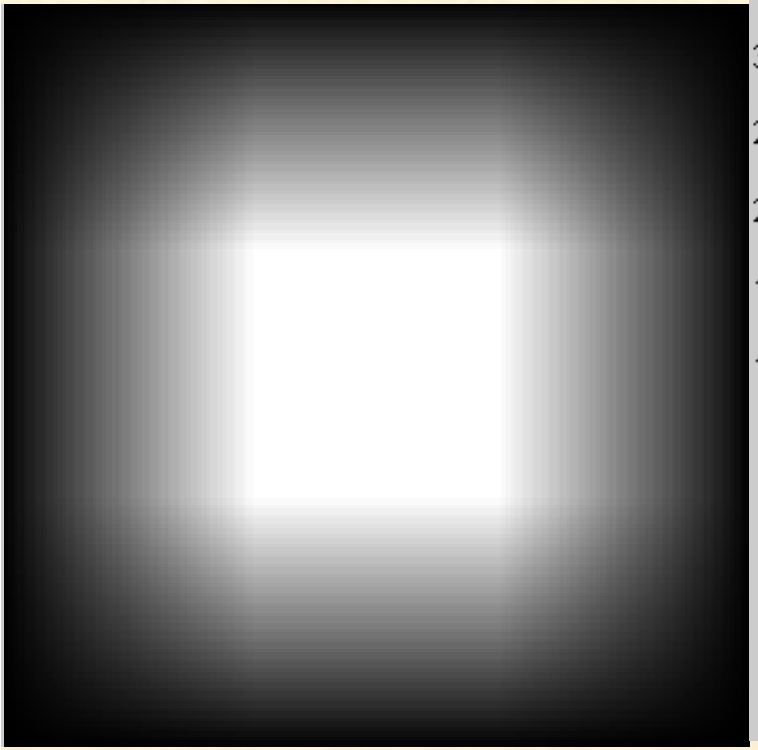
$$2-D:\ m \bullet f(x,y) = \sum_i \sum_j f(x+i,y+j)m(i,j)$$

If we take two functions f and g, as 2-D equivalent of 1-D top-hat functions, (call them as roof-top functions):

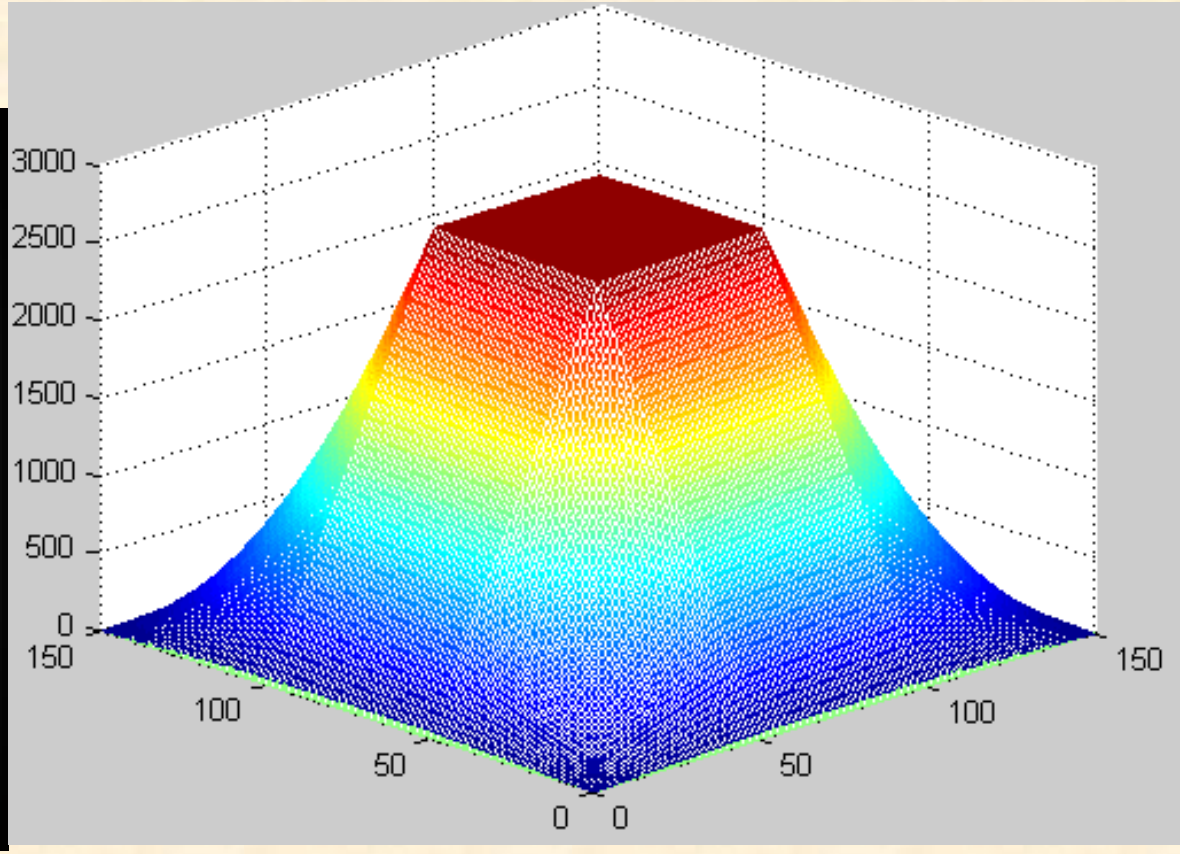
Then the 2D convolution of the functions will result in:

Results displayed as:

Image



Surface Plot



This computation is very time consuming and expensive for large size images.

If the image resolution is 32*32 or less than 64*64, it is recommended to use the above code (i.e. convolve in the spatial domain).

Generally most digital images are larger in size. Then for computational efficiency use the *convolution theorem*:

CONVOLUTION THEOREM

In 1-D :

$$f(x) * g(x) \quad \Leftrightarrow \quad F(u) \,.\, G(u)$$

and

$$f(x) \,.\, g(x) \quad \Leftrightarrow \quad F(u) * G(u)$$

in 2-D :

$$f(x, y) * g(x, y) \quad \Leftrightarrow \quad F(u, v) \,.\, G(u, v)$$

and

$$f(x, y) \,.\, g(x, y) \quad \Leftrightarrow \quad F(u, v) * G(u, v)$$

FFT algorithm exists which computes the Fourier transform of a digitized signal efficiently. Hence it is recommended to first transform the signals to the frequency domain, multiply and then compute the inverse transform to obtain the convolution. Since FFT is computationally efficient, this method works faster for large images/signals.

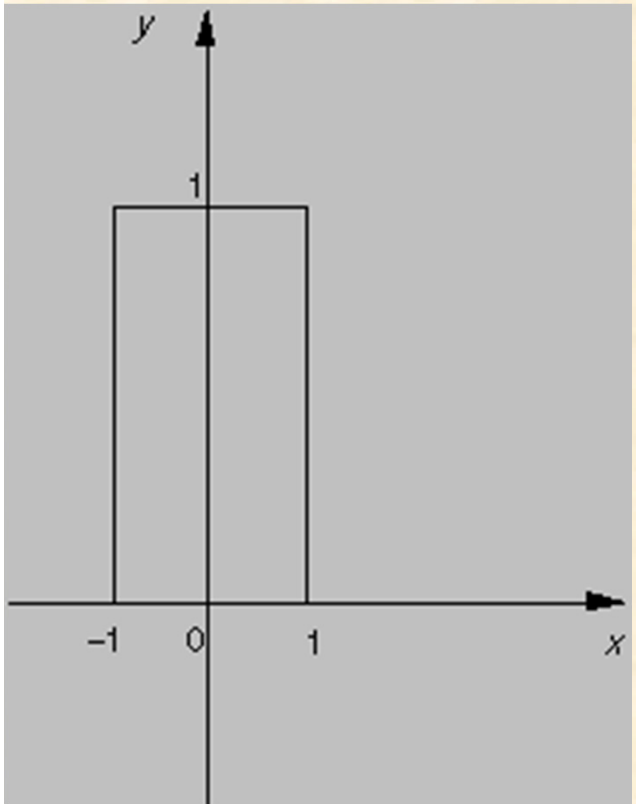
Periodicity of Convolution

Discrete 1-D case

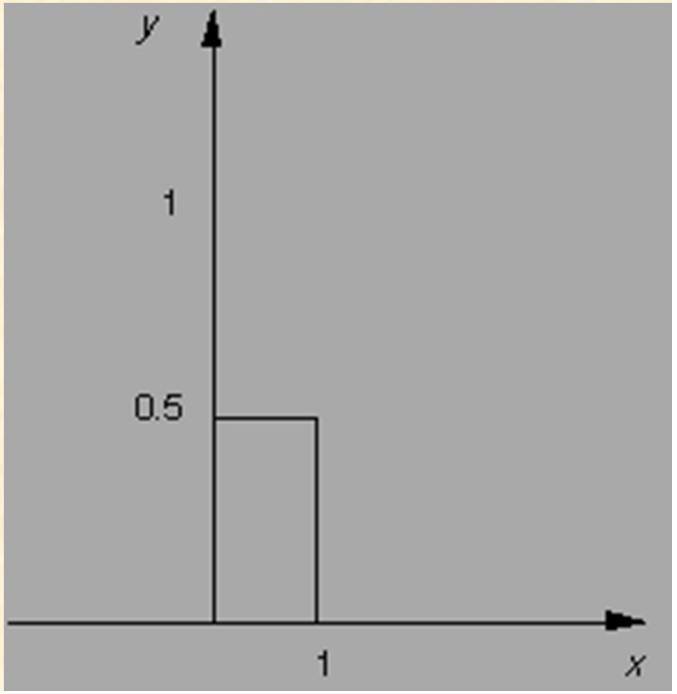
- **Consider two sequences**

$$f(x) \Rightarrow \{f(0), f(1), f(2), \ldots f(A-1)\}$$

$$g(x) \Rightarrow \{g(0), g(1), g(2), \ldots g(B-1)\}$$



What is the period of the resulting convolution ?



Periodicity of Convolution

Discrete 1-D case

- **Consider two sequences**

$$f(x) \Rightarrow \{f(0), f(1), f(2), \ldots f(A-1)\}$$
$$g(x) \Rightarrow \{g(0), g(1), g(2), \ldots g(B-1)\}$$

What is the period of the resulting convolution ?

- **Assume *f(x)* and *g(x)* are periodic with period M**

$$M \geq A + B - 1$$

- **Else wrap around error occurs, as individual periods of the convolution will overlap**

- **Hence we obtain the extended functions by padding zeros**

$$f_e(x) = \begin{cases} f(x) & 0 \le x \le A\text{-}1 \\ 0 & A \le x \le M\text{-}1 \end{cases}$$

$$g_e(x) = \begin{cases} g(x) & 0 \le x \le B\text{-}1 \\ 0 & B \le x \le M\text{-}1 \end{cases}$$

- **The convolution is given by**

$$c_e(x) = f_e(x) * g_e(x)$$

$$= \sum_{m=0}^{M-1} f_e(m) g_e(x-m) \qquad \text{for } x = 0,1,\ldots M-1$$

- **e(x) is a discrete, periodic array of length M**

2-D convolution

- **Corresponding to the 1-D continuous convolution formula**

$$c_e(x,y) = f(x,y) * g(x,y)$$
$$= \iint f(\alpha,\beta) g(x-\alpha, y-\beta)\, d\alpha\, d\beta$$

- **Correspondence between the convolution of two functions and their Fourier transform**

$$f(x,y) * g(x,y) \Leftrightarrow F(u,v)G(u,v)$$
$$f(x,y)g(x,y) \Leftrightarrow F(u,v) * G(u,v)$$

2-D Discrete Convolution

- ***f(x,y)*** **is of size A x B**
- ***g(x,y)*** **is of size C x D**
- $c_e(x,y)$ **is of size M x N**

$$M \geq A + C - 1$$

$$N \geq B + D - 1$$

- **The extended sequences are**

$$f_e(x,y) = \begin{cases} f(x,y) & 0 \leq x \leq A\text{-}1, \quad 0 \leq y \leq B\text{-}1 \\ 0 & A \leq x \leq M\text{-}1, \quad B \leq y \leq M\text{-}1 \end{cases}$$

$$g_e(x,y) = \begin{cases} g(x,y) & 0 \leq x \leq C\text{-}1, \quad 0 \leq y \leq D\text{-}1 \\ 0 & \mathrm{C} \leq x \leq M\text{-}1, \quad \mathrm{D} \leq y \leq M\text{-}1 \end{cases}$$

- **The 2-D convolution formula**

$$c_e(x,y) = f_e(x,y) * g_e(x,y)$$

$$= \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f_e(m,n)g_e(x-m,y-n)$$

$$For \;\; x = 0,1,...M-1 \;\; \& \;\; y = 0,1,...N-1$$

- **Perform 2D-DFT of the $f_e(x,y)$ and $g_e(x,y)$**
- **Multiply the two**
- **Take the 2D-IDFT**
- **We obtain the same convolution function**

Correlation

- **The 1-D correlation formula is given by**

$$f \circ g = \int_{-\infty}^{\infty} f^*(\alpha) g(x+\alpha)\ d\alpha$$

- ***g(x)* is not flipped about the origin**
  - **The Discrete case 1-D correlation formula is given by**

$$f_e \circ g_e = \sum_{m=0}^{M-1} f_e^*(m) g_e(x+m)$$

$$for \quad x = 0,1,....M-1$$

2-D Discrete Correlation

- **The 2-D correlation formula is given by**

$$f \circ g = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f^*(\alpha, \beta) g(x+\alpha, y+\beta)\ d\alpha\ d\beta$$

- **The Discrete case 2-D correlation formula is given by**

$$f_e \circ g_e = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f_e^*(m,n) g_e(x+m, y+n)$$

$$for \quad x = 0,1,....M-1 \quad and \quad y = 0,1,...N-1$$

- **If $f = g$ then we get an *Autocorrelation function***
- **Relationship between correlation of two functions and their Fourier Transform is given by**

$$f \circ g \Leftrightarrow F^*(u,v)G(u,v)$$

$$f^*.g \Leftrightarrow F(u,v) \circ G(u,v)$$

- **Application of correlation**
  - **Template or Prototype matching**
  - **Energy Computation (Parseval's Theorem)**

Equation for filtering: Use convolution theorem

Input Image to be filtered: f(x,y)
Output filtered Image: g(x,y)

Obtain g(x,y) using: G(u,v) = H(u,v).F(u,v),

where, H(u,v) is the filter transfer function, F(u,v) is the DFT of the image, and G(u,v) is the DFT of the output filtered image. Obtain g(x,y), by IDFT of G(u,v).

For bandpass filtering, the transfer function is:

$$H(u,v) = \begin{cases} 1 & \text{if } D1 \le D(u,v) \le D_2 \\ 0 & \text{otherwise} \end{cases}$$

For bandstop filtering, the transfer function is:

$$H(u,v) = \begin{cases} 0 & \text{if } D1 \le D(u,v) \le D_2 \\ 1 & \text{otherwise} \end{cases}$$

Discrete Sampling as convolution

Assume f(x,y) to be continuous and the δ function has the property:

$$\int_{-\infty}^{\infty} a\delta(x) f(x) dx = af(0)$$

Then the discretized signal $f_d(x,y)$ is:

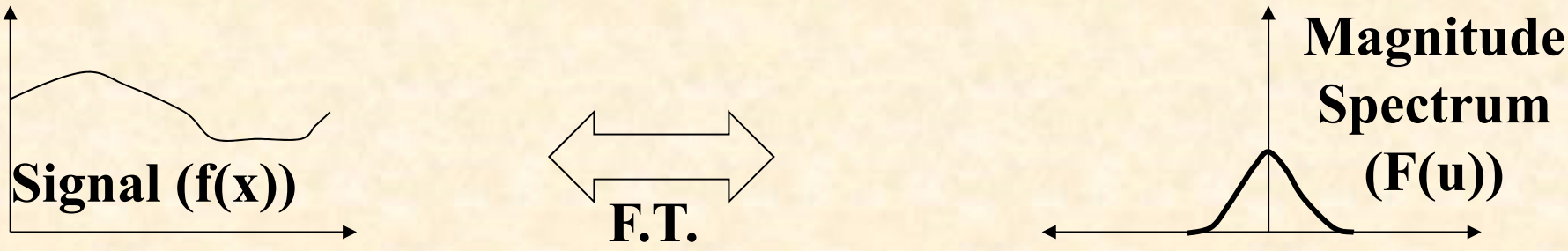
$$f_d(x,y) = \sum_{i=-\infty}^{\infty}\sum_{i=-\infty}^{\infty} f(i,j)\delta(x-i, y-j)$$

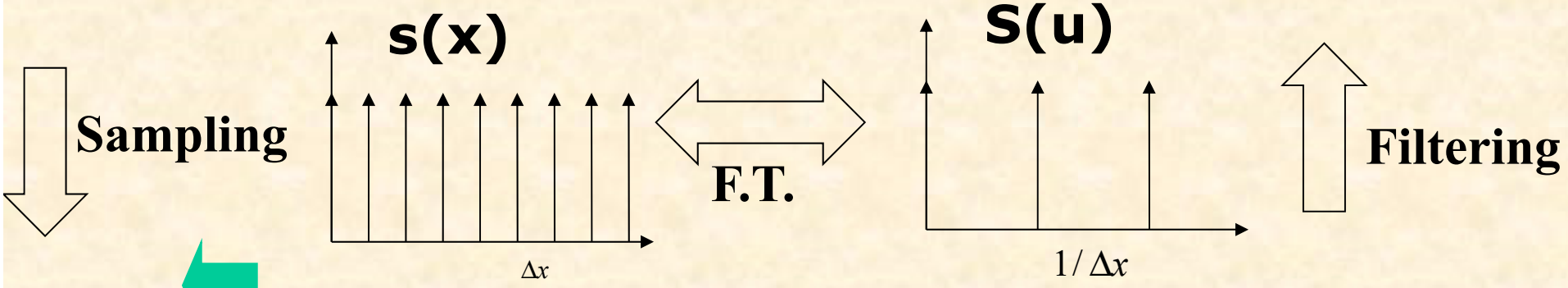
$$= f(x,y)[\sum_{i=-\infty}^{\infty}\sum_{i=-\infty}^{\infty} \delta(x-i, y-j)]$$

Multiply the signal by a set of δ functions, one at each sample point.

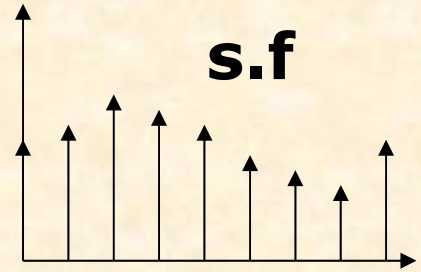
This is called a *Comb* function in 1D and *Bed of nails* in 2D.

Sampling and Aliasing:





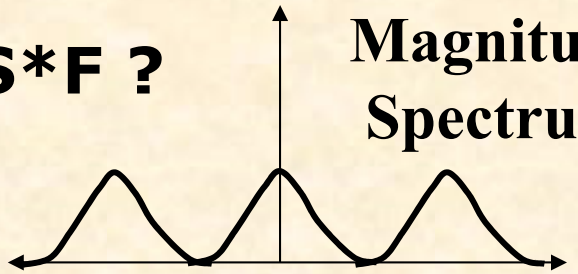
$$N.\Delta u = 1/(\Delta x);$$



Sampled Signal

DFT

S*F ?



Draw for various Δx values

The Fourier transform of a sampled signal :

If : $f_d(x,y) = f(x,y).comb_{2D}(,)$

$$\Im\{f_d(x,y)\} = \Im\{f(x,y)[\sum_{i=-\infty}^{\infty}\sum_{i=-\infty}^{\infty}\delta(x-i,y-j)]\}$$

$$= \Im\{f(x,y)\} * \Im\{[\sum_{i=-\infty}^{\infty}\sum_{i=-\infty}^{\infty}\delta(x-i,y-j)]\}$$

$$= F(u,v) * [\sum_{i=-\infty}^{\infty}\sum_{i=-\infty}^{\infty}\delta(u-i,v-j)]\}$$

$$= \sum_{i=-\infty}^{\infty}\sum_{j=-\infty}^{\infty} F(u-i,v-j)$$

$$f_d(x) = f(x).comb_{1D}(x)$$

$$\Im\{f_d(x)\} = \Im\{f(x)[\sum_{i=-\infty}^{\infty}\delta(x-i)]\}$$

$$= \sum_{i=-\infty}^{\infty} F(u-i)$$

The Fourier transform of a sampled signal (exact Exprsn.):

$$X(e^{j\omega}) = \frac{1}{T}\sum_{k=-\infty}^{\infty} X_a[(j(\Omega - \frac{2\pi k}{T})]\Big|_{\Omega=\omega/T};$$

T is the sampling period (spacing), and
2π/T is the sampling frequency (rate);

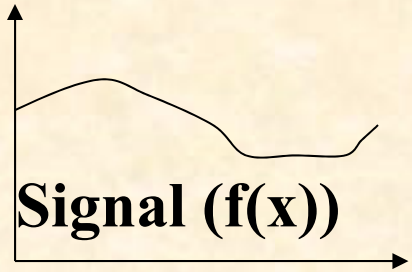
$X(e^{j\omega})$ is the FT of x[n];

$X_a(j\Omega)$ is the FT of $x_a(t)$;

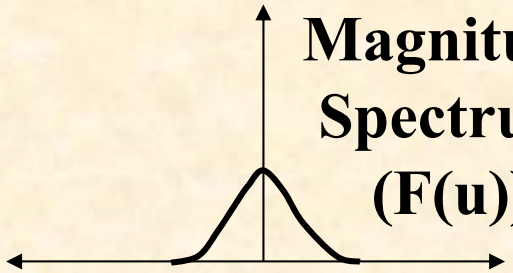
x[n] is the sampled version of $x_a(t)$;

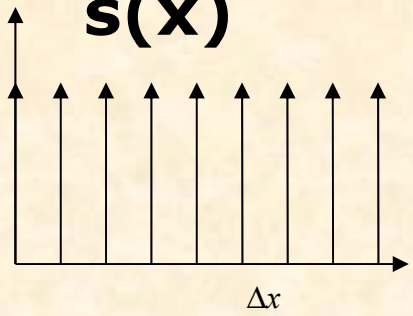
ω is in radians; Ω is in kilo-radians
(assuming T is in m-sec.)

Sampling and Aliasing



F.T.

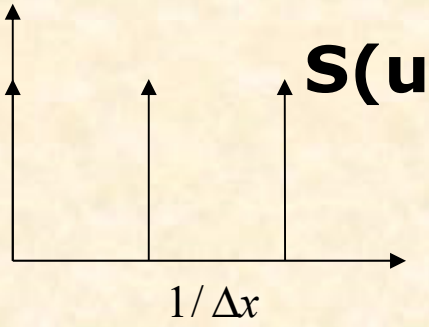




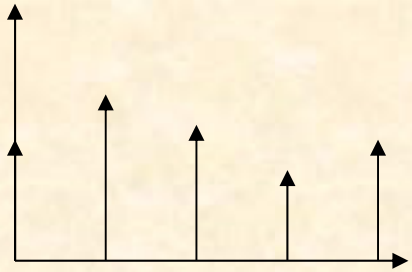
Sampling

F.T.

Filtering

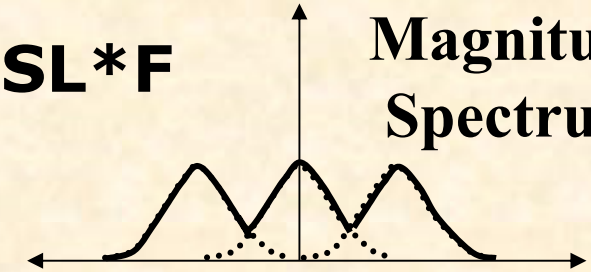


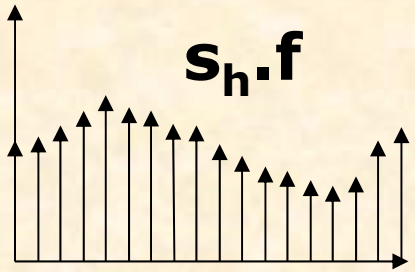
$N.\Delta u = 1/(\Delta x);$



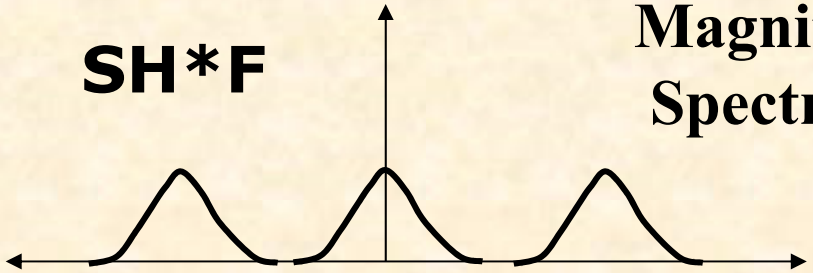
Sampled Signal

DFT

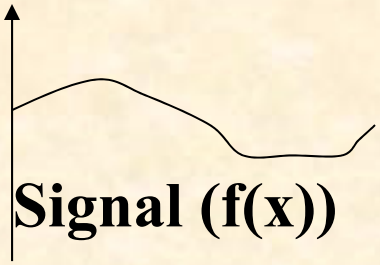




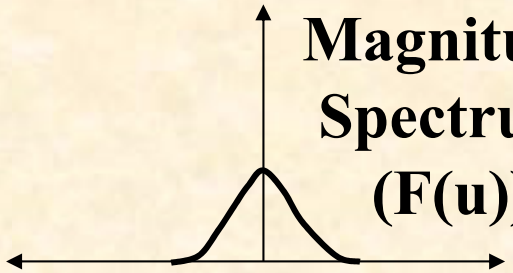
Sampled Signal



Sampling and Aliasing



F.T.



$F(u) = FLTR.SHF;$

where,

$FLTR = ??$

$FLTR = rect(u)$

or BOX function in 2 - D

Sampling

Filtering

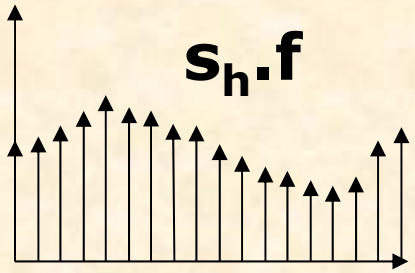
If,

$F(u) = RECT\ .\ SHF;$

Courtesy Convolution theorem :

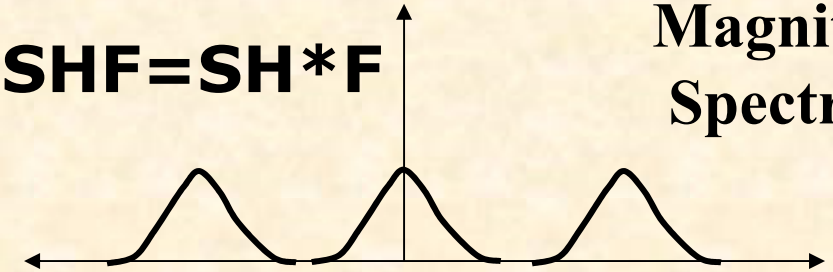
f(x) = ?? ⊗ shf;

Fill in the gap above

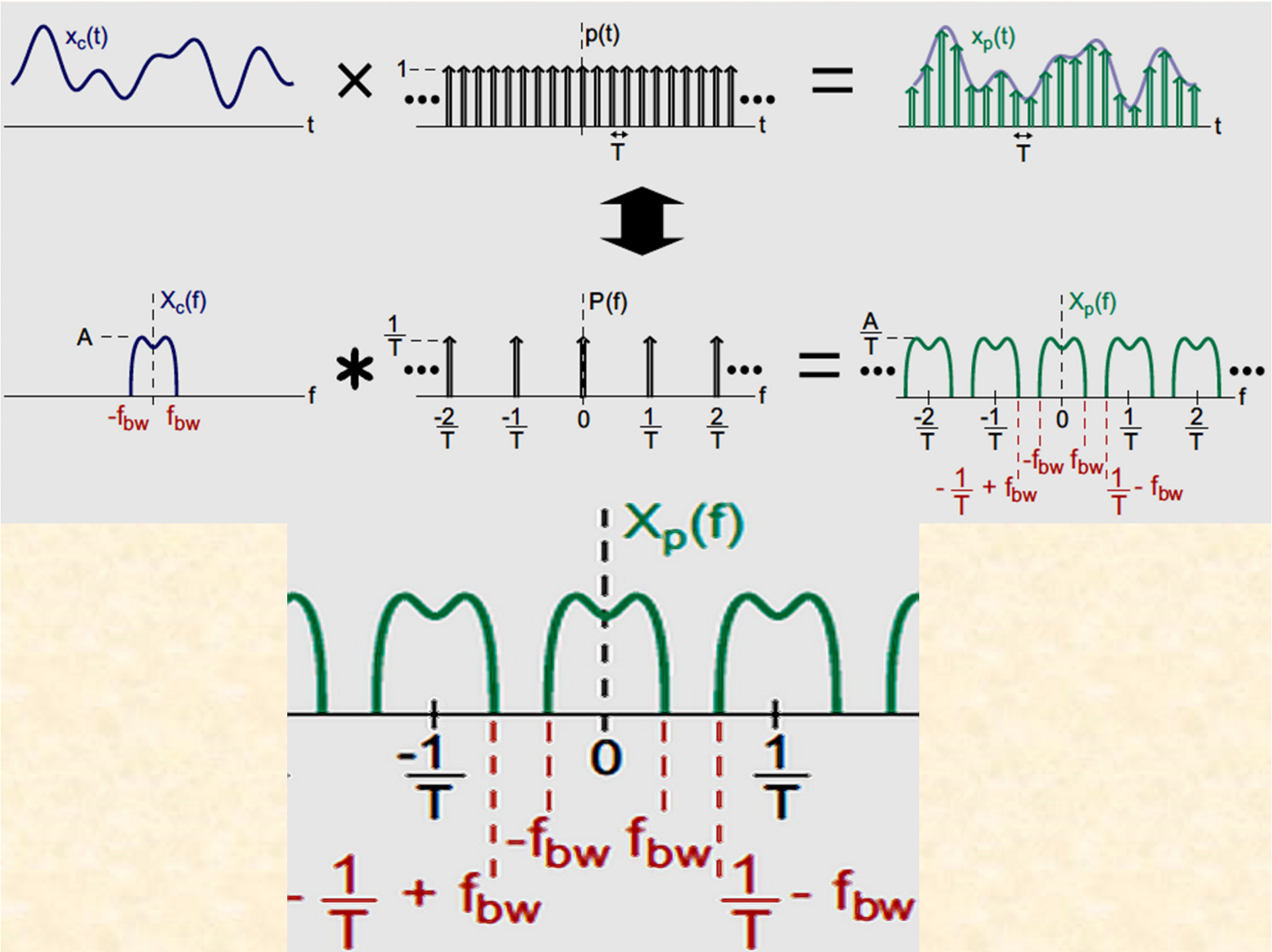


Sampled Signal

SHF=SH*F



Magnitude
Spectrum

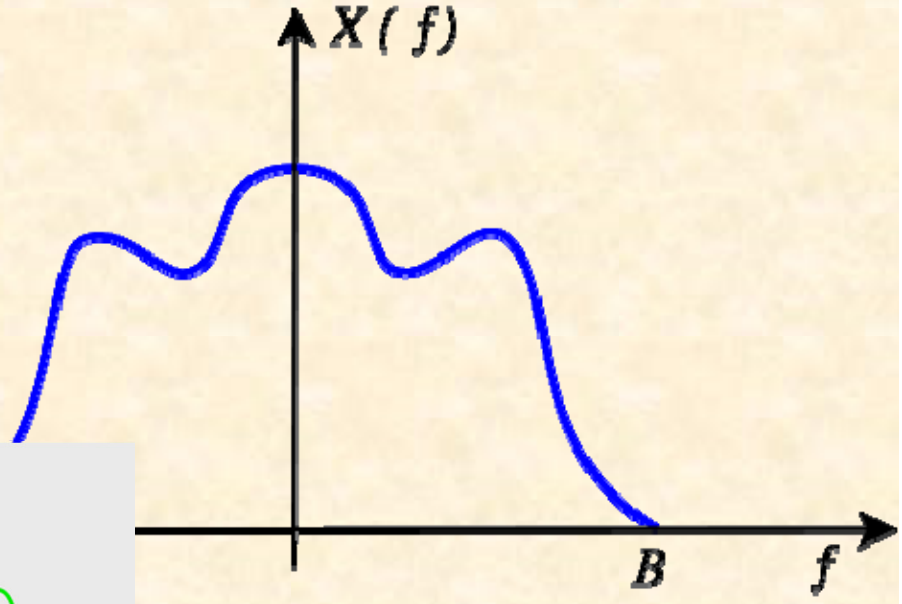

$x_c(t)$
t
×
p(t)
1
T
=
$x_p(t)$
$X_c(f)$
A
$-f_{bw}$ f_{bw}
f
*
P(f)
$\frac{1}{T}$
$\frac{-2}{T}$ $\frac{-1}{T}$ 0 $\frac{1}{T}$ $\frac{2}{T}$
=
$X_p(f)$
$\frac{A}{T}$
$-\frac{1}{T} + f_{bw}$
$\frac{1}{T} - f_{bw}$

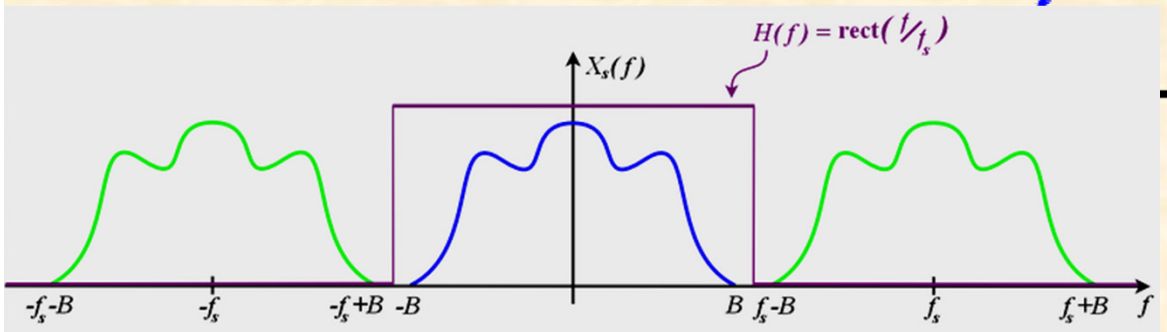
Shannon's version of the theorem states:

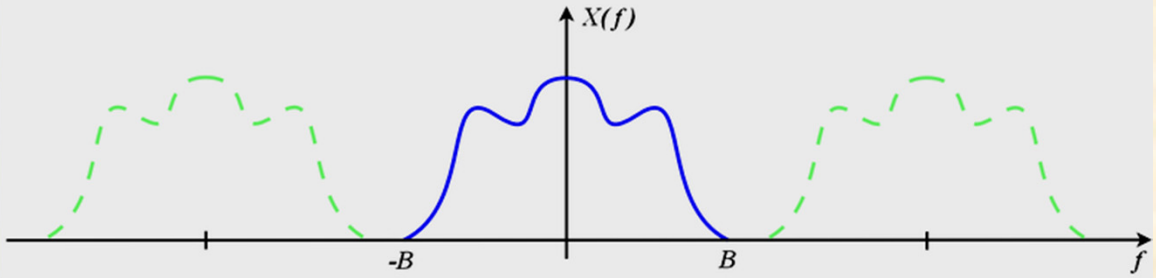
If a function *x*(*t*) contains no frequencies higher than *B* hertz, it is completely determined by giving its ordinates at a series of points spaced 1/(2*B*) seconds apart.

Thus, the sampling theorem of Shannon-Nyquist:

$$\Delta X \leq 1/2B$$







Shannon's interpolation formula and Whittaker's interpolation formula, states that: under certain *limiting conditions*, a function $x(t)$ can be recovered exactly from its samples;

$x[n] = x(nT)$, by the Whittaker–Shannon interpolation formula:

$$x(t) = \sum_{n=-\infty}^{\infty} x[n] \cdot \operatorname{sinc}\left(\frac{t - nT}{T}\right)$$

Interpolation as convolution sum:

The interpolation formula is derived in the Nyquist–Shannon sampling theorem article, which points out that it can also be expressed as the convolution of an infinite impulse train with a sinc function:

$$x(t) = \left(\sum_{n=-\infty}^{\infty} x[n] \cdot \delta\left(t - nT\right)\right) * \operatorname{sinc}\left(\frac{t}{T}\right).$$

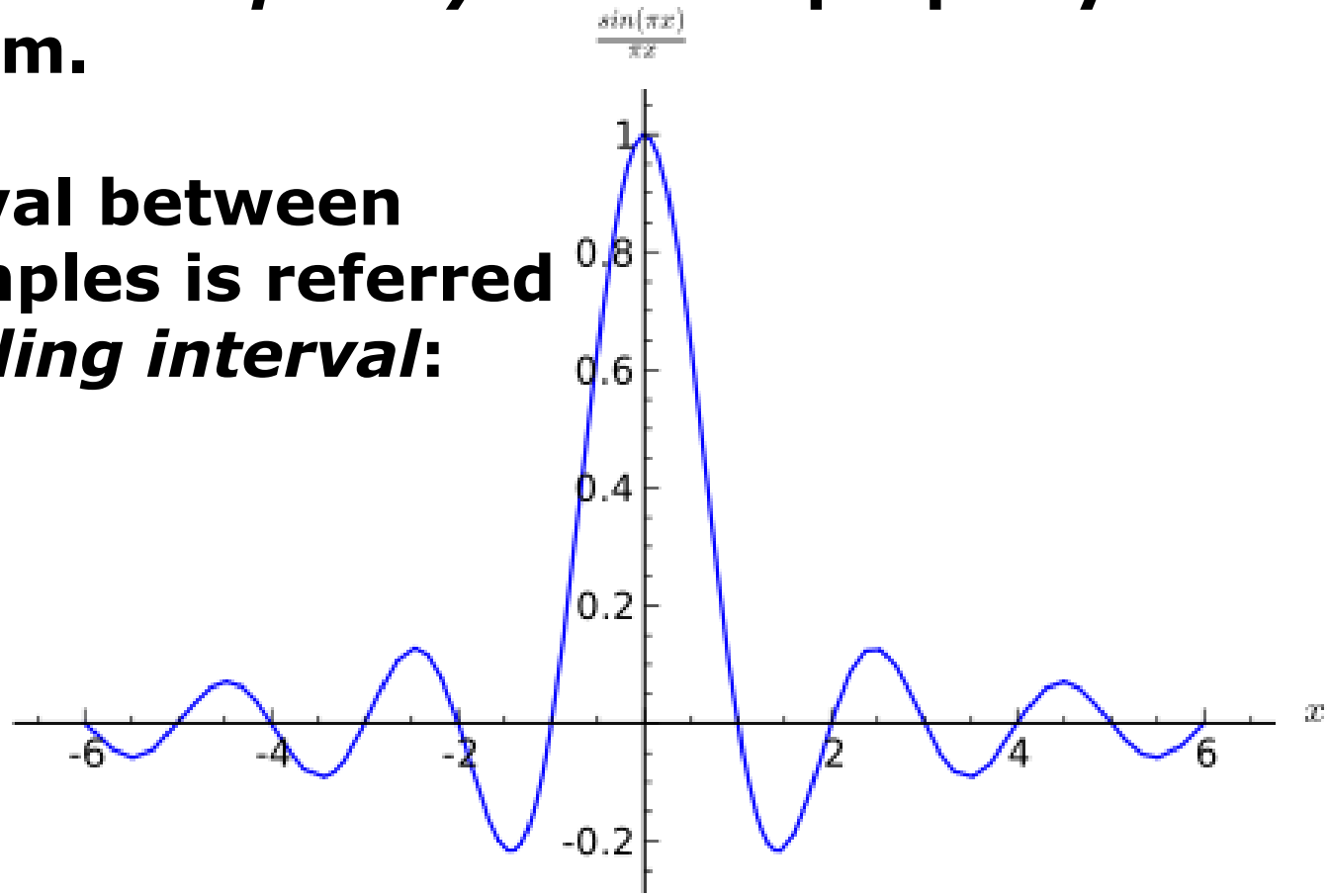
This is equivalent to filtering the impulse train with an ideal (brick-wall) low-pass filter.

The sufficient condition for exact reconstructability from samples at a uniform sampling rate f_s (in samples per unit time) is: $f_s > 2B.$

The quantity 2*B* is called the *Nyquist rate* and is a property of the bandlimited signal, while $f_s/2$ is called the *Nyquist frequency* and is a property of the sampling system.

The time interval between successive samples is referred to as the *sampling interval*:

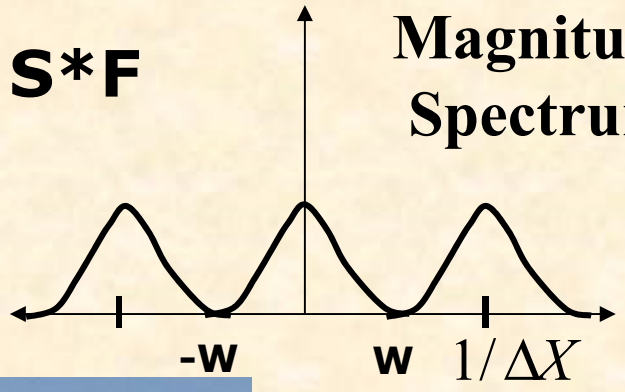
$$T \stackrel{\text{def}}{=} \frac{1}{f_s},$$



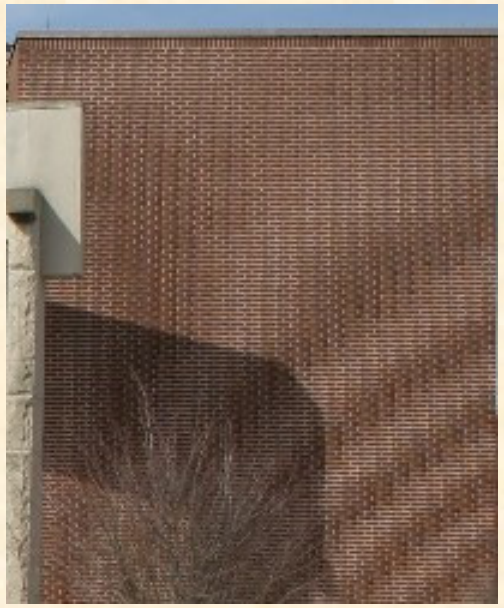
Thus, the sampling theorem of Shannon-Nyquist:

$$\Delta X \leq 1/2W$$

S*F

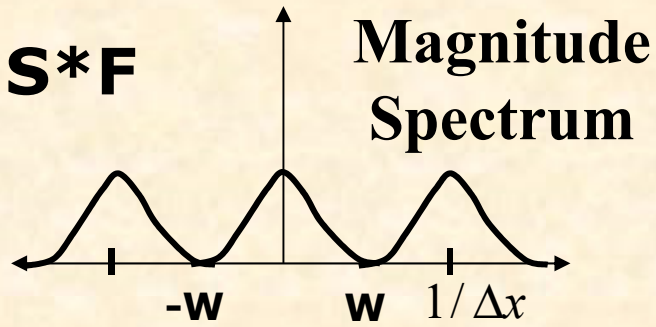


Magnitude Spectrum



Thus, the sampling theorem of Shannon:

$$\Delta x \leq 1/2W$$



Also read about:

- **Walsh Transform**
- **Hadamard Transform**
- **DCT**
- **Haar Transform**
- **Slant Transform**
- **Hilbert Transform**
- **Z- and Laplace Transform**
- **Chirplet Transform**

References

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5. “Algorithms for Image Processing and Computer Vision”; J. R. Parker; John Wiley and Sons; 1997+.